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Carl-Cranz-Gesellschaft e.V.

Gesellschaft für technisch-wissenschaftliche Weiterbildung

Sensor-Datenfusion

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Fusion: Optical/SAR

Fusion: Optical/SAR

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Motivation: Need for new and high quality products

- Why? Complementary nature of sources
- How?
  - Learn (understand) semantic relationships between objects
  - Develop methodology

Data Fusion: Definition

Data fusion is a formal framework in which are expressed the means and tools for the alliance of data originating from different sources.

It aims at obtaining information of greater quality; the exact definition of 'greater quality' will depend upon the application (Wald, L., 1999)

Data fusion is application dependent

Wald L., 1999. Some terms of reference in data fusion. **IEEE Transactions on Geosciences and Remote Sensing**, 37(3), 1190-1193

Content

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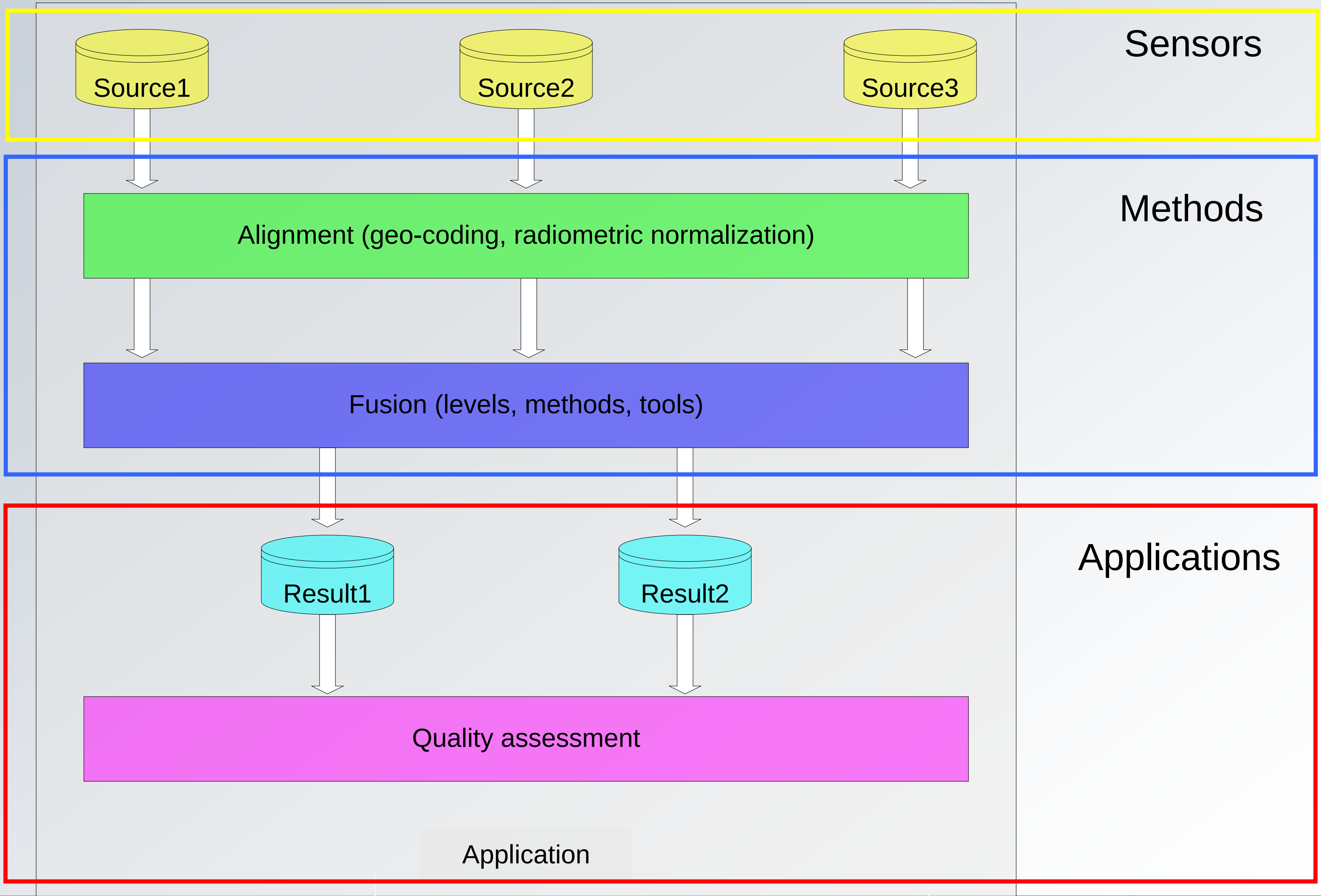
- Data fusion concept
- Data pre-processing
  - General fusion framework GFF
  - Orthogonal acquisition geometry
- Data fusion framework INFOFUSE
- Examples for optical/SAR classification
- Simulation of images
- Conclusions and outlook

Data Fusion: Concept



Optical/SAR data fusion

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- Pre-processing
  - Orthogonal acquisition geometry
    - to minimize displacement effects
  - Ortho-rectification
    - DEM used
    - optical data enhancement using TS-X GCPs [1]
  - Co-registration of optical/SAR data
    - using mutual information [2]
  - Pan-sharpening of multi-spectral and panchromatic optical data
    - General Fusion Framework
  - De-speckling of SAR imagery
- Feature extraction
- Classification
- Simulation

[1] Reinartz, P., Müller, R., Schwind, P., Suri, S. and Bamler, R., 2011. Orthorectification of VHR optical satellite data exploiting the geometric accuracy of TerraSAR-X data. **ISPRS Journal of Photogrammetry and Remote Sensing**, 66, 124-132.

[2] Suri, S. and Reinartz, P., 2010. Mutual-Information-Based Registration of TerraSAR-X and Ikonos Imagery in Urban Areas. **IEEE Transactions on Geoscience and Remote Sensing** 48(2), 939-949.

Pansharpening

- Pre-processing
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Pan-sharpening

Input

Low resolution image (multispectral, hyperspectral, …)
High resolution image (panchromatic, SAR, …)

Aim

Include spatial information from high resolution image while preserving spectral properties of low resolution image

General Fusion Framework GFF

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Method

Interpolation $msi = \mathrm{I}(ms)$

Fusion $msf = \mathrm{F}(msi, pan)$

Histogram matching $msf = \mathrm{H}(msf, ms)$

Spectral Fusion SF

How?

Add **only** high frequency information from high resolution image to low resolution image

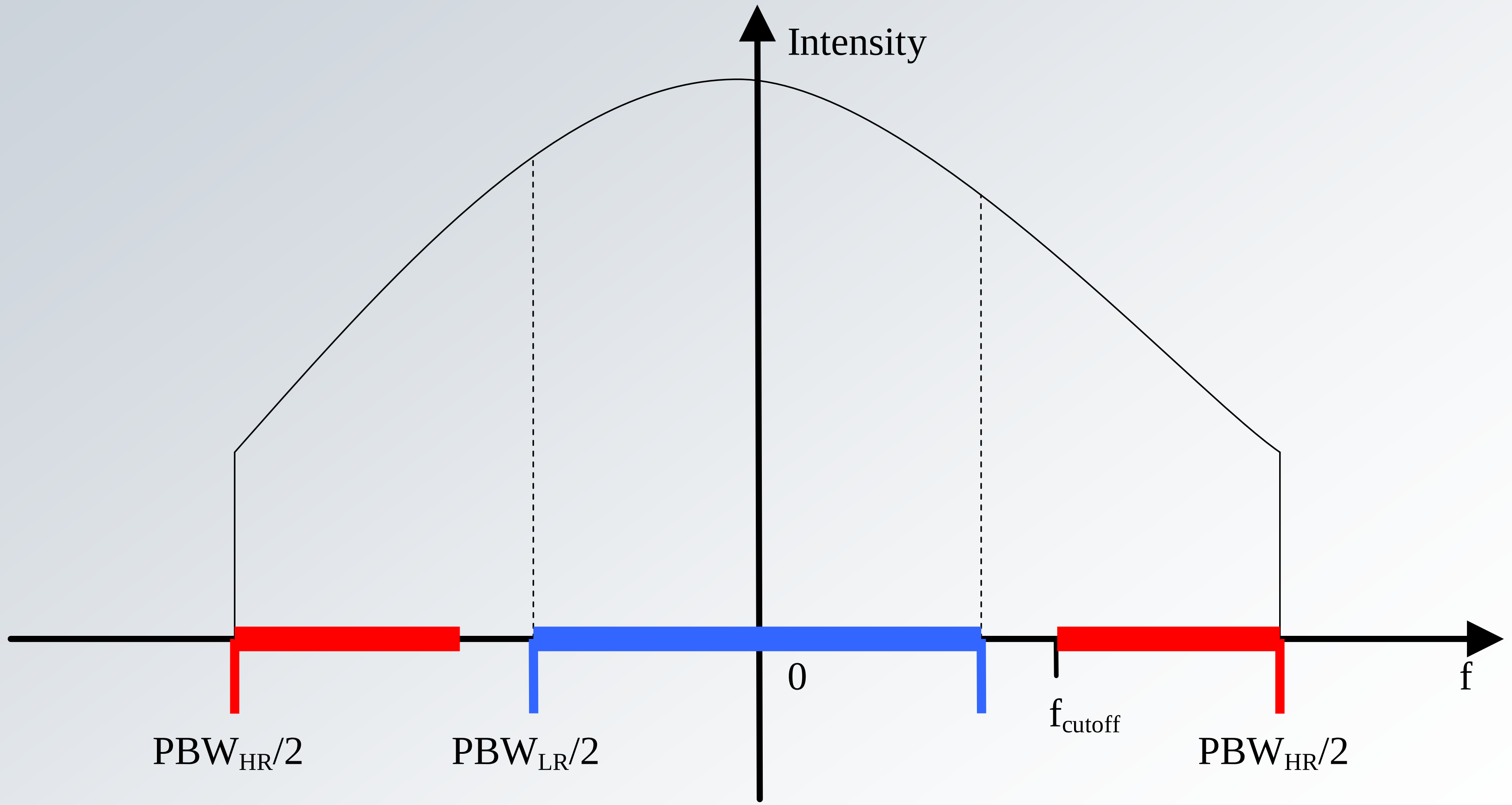
Solution

Fourier/spectral domain

Interpolation and fusion in one step

Palubinskas, G. and Reinartz, P., 2011. Multi-resolution, multi-sensor image fusion: general fusion framework, **Proc. of Joint Urban Remote Sensing Event JURSE**, 11-13 April, 2011, Munich, Germany, IEEE, 313-316.

Spectral Fusion SF



Spectral Fusion SF

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Fourier transform

$$MS = \mathrm{FFT}(ms)$$

$$PAN = \mathrm{FFT}(pan)$$

Zero padding and windowing

$$MSI = \mathrm{ZP}(W \cdot MS)$$

Frequency addition

$$MSF = MSI + PAN \cdot HPF$$

$$MSF = MSI + PAN \cdot (1 - LPF)$$

Inverse Fourier transform

$$msf = FFT^{-1}(MSF)$$

Spectral Fusion SF

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Signal domain $$msf = msi + pan * hpf$$

where $$hpf = FFT^{-1}(HPF)$$

or $$msf = msi + pan - pan * lpf$$

J. Hill, C. Diemer, O. Stover, and T. Udelhoven, 1999. A local correlation approach for the fusion of remote sensing data with different spatial resolution in foresty applications, **Proc. of Int. Archives of Photogrammetry and Remote Sensing**, Valladolid, Spain, June 3-4. 1999, Vol. 32, No. Part 7-4-3 W6, pp. 167–174.

WV-2 pan-sharpening (München)

CCG
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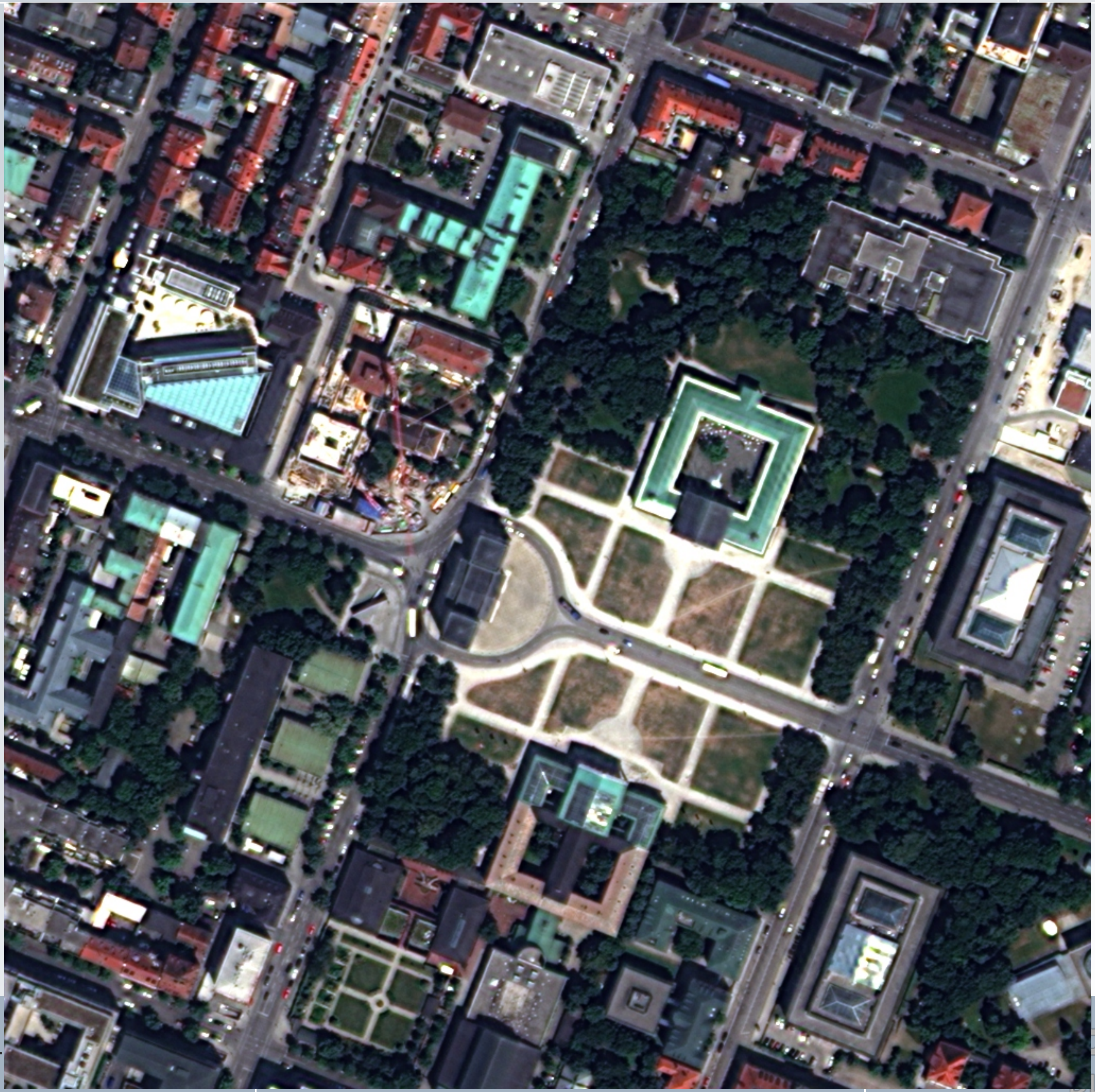

TS-X Radar-sharpening (München)

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WV-1

rg

az

TS-X

rg

az

Orthogonal acquisition geometry

- Pre-processing
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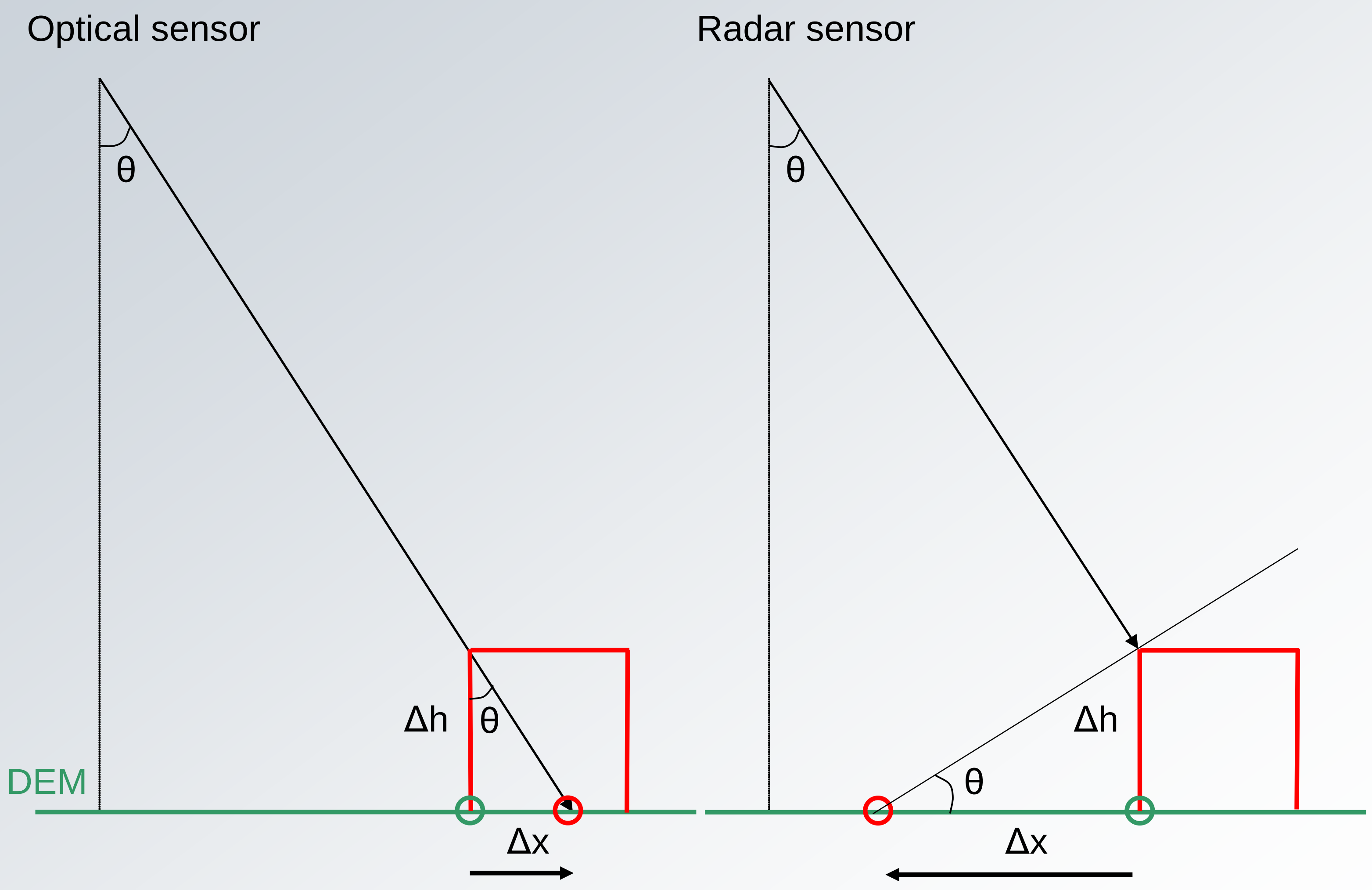
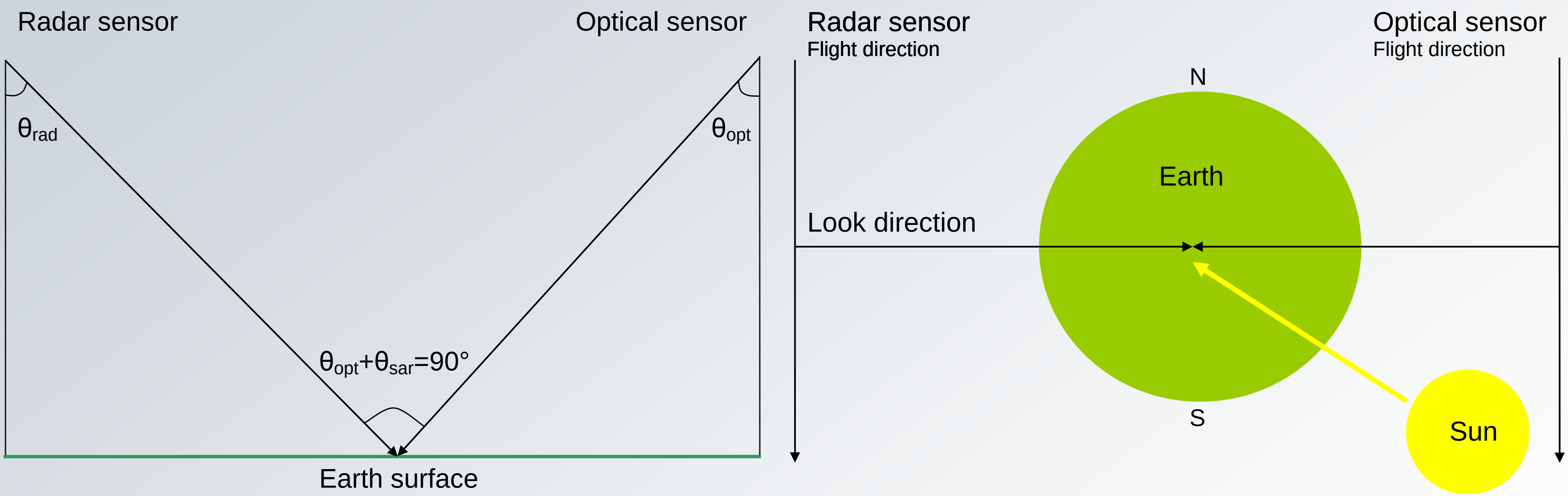
3D Object height



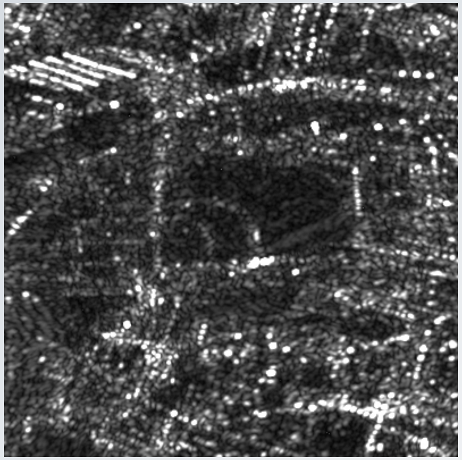
Orthogonal acquisition geometry



Palubinskas, G., Reinartz, P. and Bamler, R., 2010. Image acquisition geometry analysis for the fusion of optical and radar remote sensing data. **International Journal of Image and Data Fusion**, 1(3), 271-282

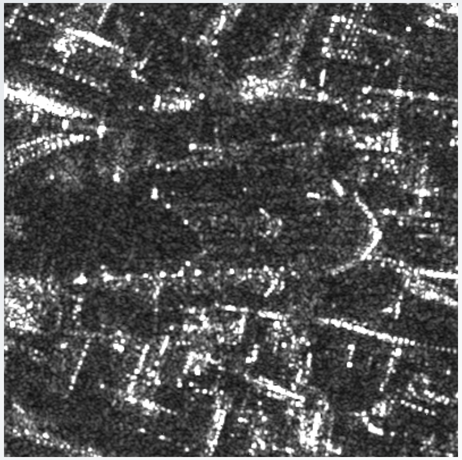
Two pairs of Optical/SAR acquisition

IKONOS2



TS-X ascending

WV-1



TS-X descending

Classification

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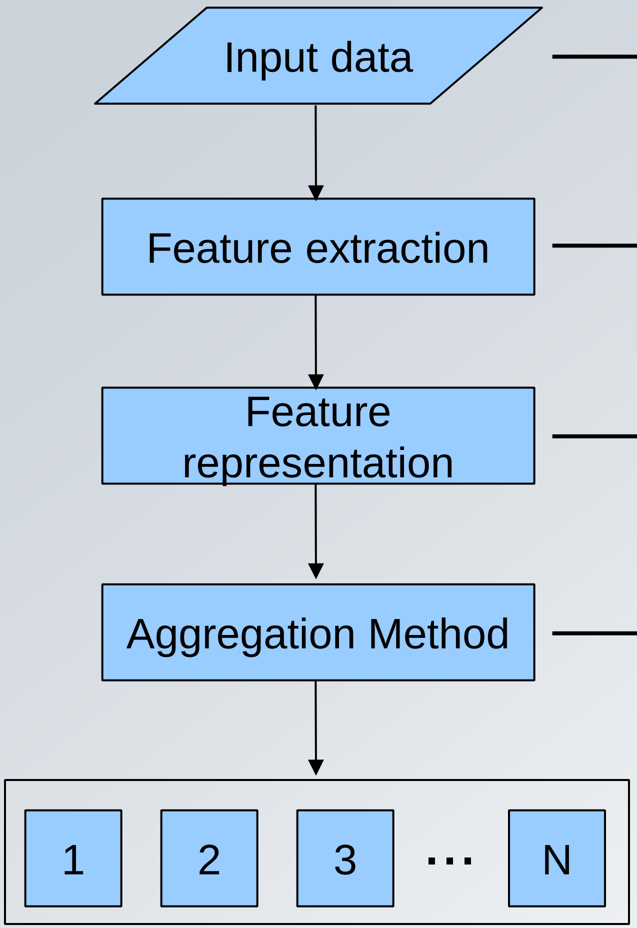
Data fusion framework INFOFUSE



Input multisensory data: Multispectral, SAR, GIS, DEM, etc.

Information fission: extraction of exhaustive set of features (e.g. Gabor, Co-Occurrence)

Feature representation on predefined discrete domain using unsupervised clustering

Neural network, Bayesian network, Graphical model

Selected classes

Palubinskas, G. and Datcu, M., 2008. Information fusion approach for the data classification: an example for ERS-1/2 InSAR data. **International Journal of Remote Sensing**, 29(16), 4689-4703.

Data fusion requirements and solutions

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Requirements

- to follow consensus theory*
- Data non-commensurability: to work with different input data (e.g. nature and statistics of optical and SAR)
- Arbitrary number of data sources
- Aggregation method to be able to use arbitrary number of calculated input features
- Acceptable complexity

Solutions

- Data fission is employed (to calculate exhaustive feature set). Quasi-full characterization of classes
- Feature representation on a finite predefined domain (e.g. numbers of a range). Reduce of data size
- Neural Networks, Bayesian networks, or Graphical models

*Benediktsson, J., Sveinsson, J., and Swain, P., 1997. Hybrid consensus theoretic classification, **IEEE Transactions on Geoscience and Remote Sensing**, 35(4), 833–843.

Feature aggregator selection

Feature Aggregator	Advantages	Disadvantages
Neural Network	Acceptable training time Variety of methods for learning High accuracy of classification	Overtraining
Bayesian Network	Knowledge representation in probabilistic way Proper configuration using expert knowledge	High training/classification time
Graphical model	Knowledge representation in probabilistic way (assuming multi-nominal distributions) Proper configuration using expert knowledge (compare to neural network)	High training/classification time No practical methods for structure learning

Data characteristics

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Sensor Parameter	**TerraSAR-X**	**WorldView-2**
Image time (local)	7-Jun-2008 07:17:48	12-Jul-2010 10:30:17
Mode	Spotlight HS	Pan-sharpened VNIR bands
Look angle	49.45° Right	5.2° Left
Orbit	Descending	Descending
Polarization	Single, VV	
Product	EEC	L2A
Resolution gr x az (m)	1.0 x 1.14	0.5 x 0.5
Pixel spacing (m)	0.5	0.5
Radiometric resolution	16 bit	11 bit

Experiment 1

Urban area classification:

- Munich city
- 6 classes

Features:

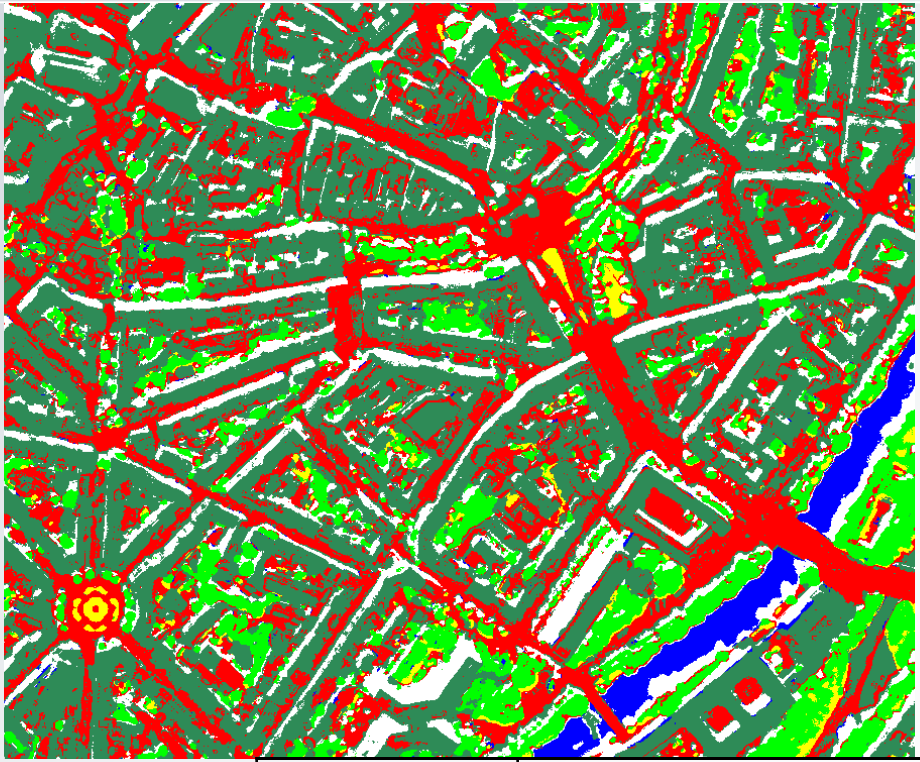
- WV-2 VNIR (4 bands)
- TS-X Texture (Co-occurrence)

Fusion strategies:

- VNIR
- VNIR+SAR Texture

Urban area classification

Optical RGB image



INFOFUSE classification

Label	Classes/subclasses
Buildings	8 subclasses
Roads	2 subclasses
Water	1 class
Forest/Trees	1 class
Grass	1 class
Shadows	1 class

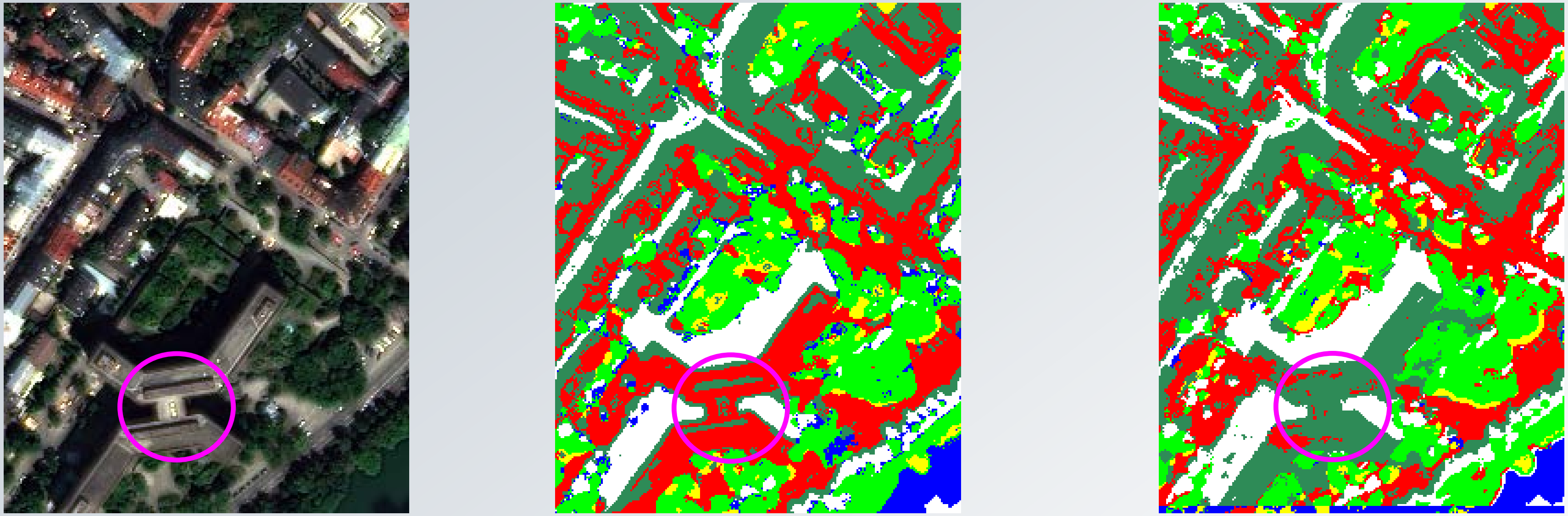
Input data:

• WorldView-2 multispectral (VNIR range)

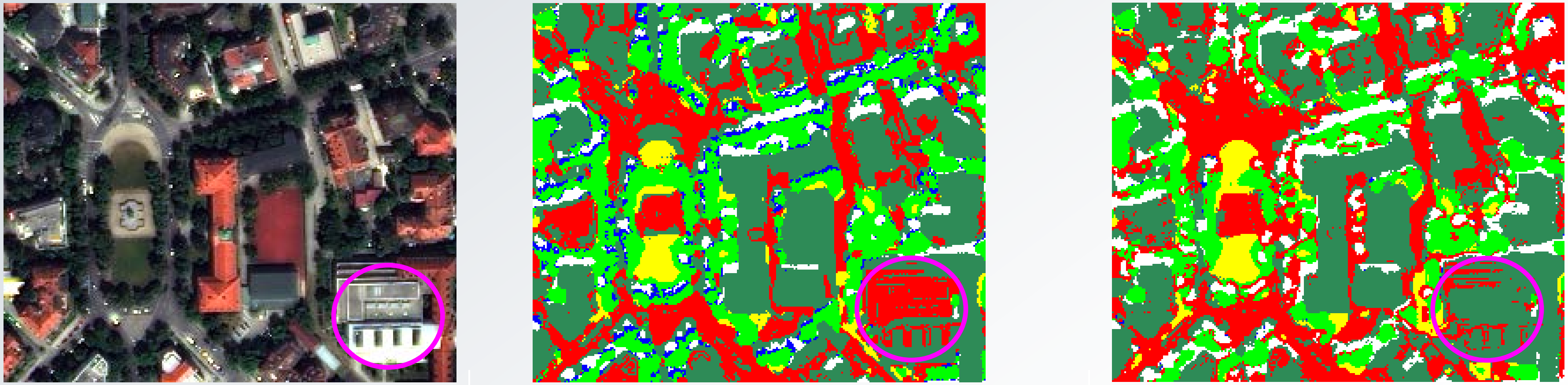
• TerraSAR-X single polarization band

Haralick texture features

Urban area classification zoom



SAR data allow to reduce errors in building/road separation



Confusion matrices

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Class	Water	Grass	Trees	Buildings	Road	Shadow
Water	100.00	0	0	0	0	0
Grass	0	85.47	0	0	0	0
Trees	0	14.53	100.00	0	0	0
Buildings	0	0	0	**60.05**	**42.25**	4.72
Road	0	0	0	**39.95**	**57.75**	0
Shadow	0	0	0	0	0	95.28
Total	100.00	100.00	100.00	100.00	100.00	100.00

Class	Water	Grass	Trees	Buildings	Road	Shadow
Water	100.00	0	0	0	0	0
Grass	0	98.20	0	0	0	0
Trees	0	1.80	98.90	0	0	0
Buildings	0	0	0	**96.36**	**3.91**	0.47
Road	0	0	1.10	**3.64**	**96.06**	0
Shadow	0	0	0	0	0	99.53
Total	100.00	100.00	100.00	100.00	100.00	100.00

INFOFUSE Multispectral (VNIR)
Overall Accuracy: 70.95%
Kappa Coefficient: 0.6059

INFOFUSE Multispectral (VNIR)+SAR
Overall Accuracy: 97.19%
Kappa Coefficient: 0.9613

Experiment 2

Urban area classification:

- Munich city
- 23 classes

Features:

- WV-2 (8 bands), Red Band Texture-Gabor (6 orientations, 4 sine modulations, 2 sigma sizes)
- TS-X Texture-Gabor (6 orientations, 4 sine modulations, 2 sigma sizes)
- DSM (Generated from WV-2 panchromatic stereo pair)

Fusion strategies:

- Multispectral, DSM (9 features),
- Texture SAR, Texture optical, DSM (97 features),
- Multispectral, Texture SAR, Texture optical (104 features),
- **Multispectral, Texture SAR, Texture optical and DSM (105 features)**

Classes

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23 classes were defined:

- 1. Water
- 2. Forest/Trees
- 3. Grass/Low vegetation
- 4. Bare soil
- 5. Construction site
- 6. Swimming pool
- 7. Asphalt road
- 8. Concrete road
- 9. Football field
- 10. Tennis field
- 11. Green house
- 12. Rail road
- 13. Tram line
- 14. Cemetery
- 15. Parking/car
- 16. Shadow
- 17. Red roofing tiles
- 18. Grey roofing tiles
- 19. Dark roofing tiles
- 20. Roofing concrete
- 21. Vegetation roof
- 22. Zinc roof
- 23. Roofing copper

Ground truth

- ATKIS vector map (Landesamt für Vermessung und Geoinformation)
- Material vector data (Dr. Wieke Heldens)

Classification accuracy

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Maximum likelihood (does not follow consensus theory)		
	OVA, %	Kappa
Multispectral, DSM (9 features)	85.4841	0.8409
Texture, DSM (97 features)	60.5719	0.5666
Multispectral, Texture (104 features)	81.4288	0.7932
Multispectral, Texture, and DSM (105 features)	82.1923	0.8019
Neural Network (1 hidden layer, 40 neurons for 97, 104, or 105 features, 8 neurons for 9 features)		
	OVA, %	Kappa
Multispectral, DSM (9 features)	85.6575	0.8426
Texture, DSM (97 features)	60.8644	0.5643
Multispectral, Texture (104 features)	82.6471	0.8076
Multispectral, Texture, and DSM (105 features)	87.0697	0.8566
INFOFUSE (based on Neural Network, 1 hidden layer, 40 neurons for 97, 104, or 105 features, 9 neurons for 8 features) (50 clusters for each feature)		
	OVA, %	Kappa
Multispectral, DSM (9 features)	85.1835	0.8360
Texture, DSM (97 features)	71.8699	0.6906
Multispectral, Texture (104 features)	88.8692	0.8768
Multispectral, Texture, and DSM (105 features)	**90.1092**	**0.8907**

Classification accuracy

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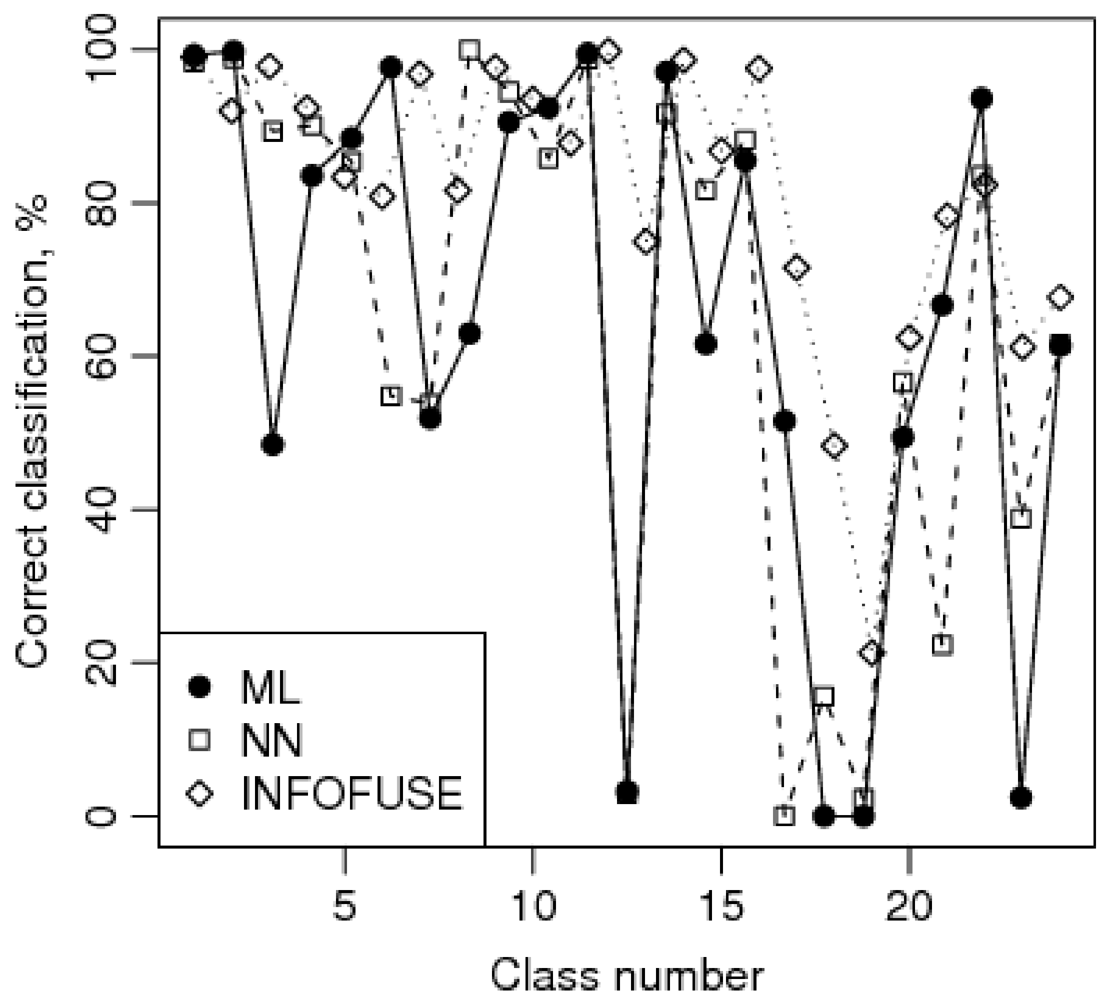
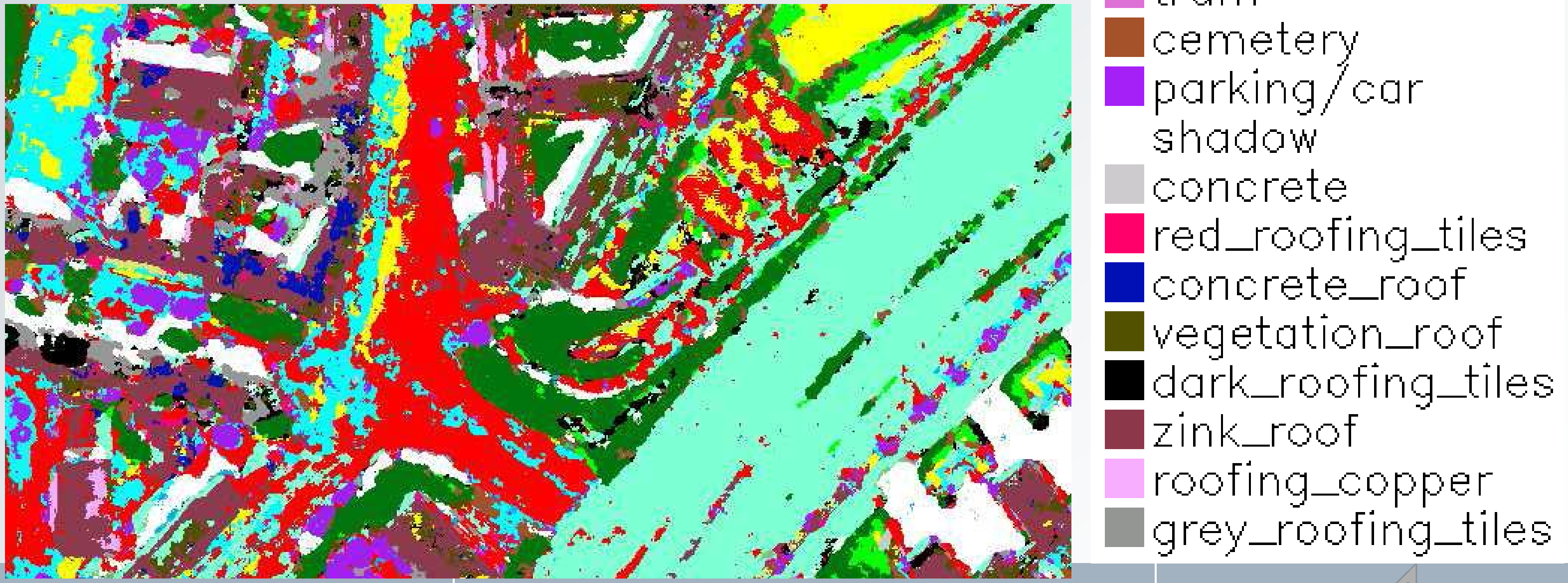
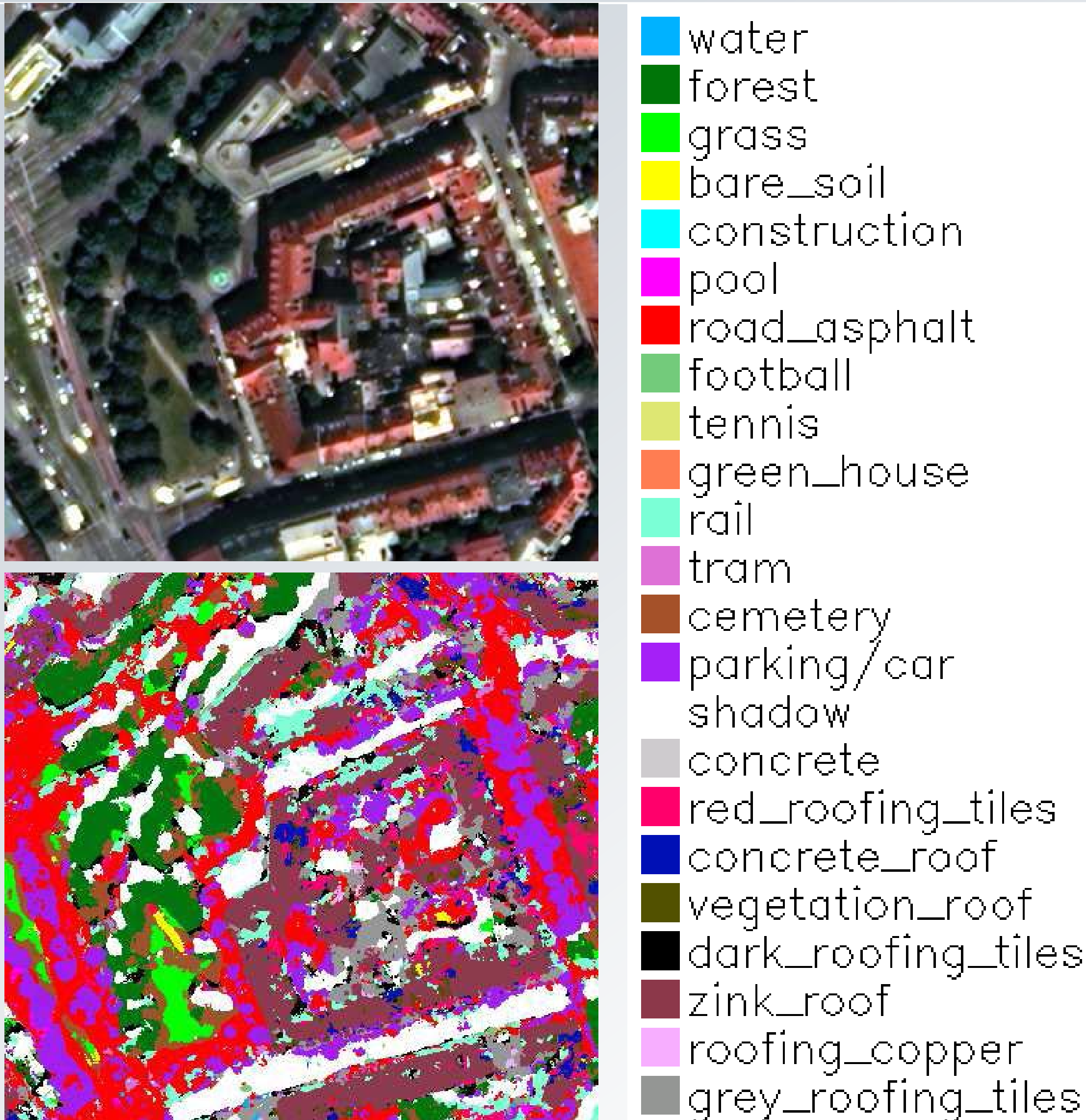


Classification map 1



Classification map 2



Classification map 3

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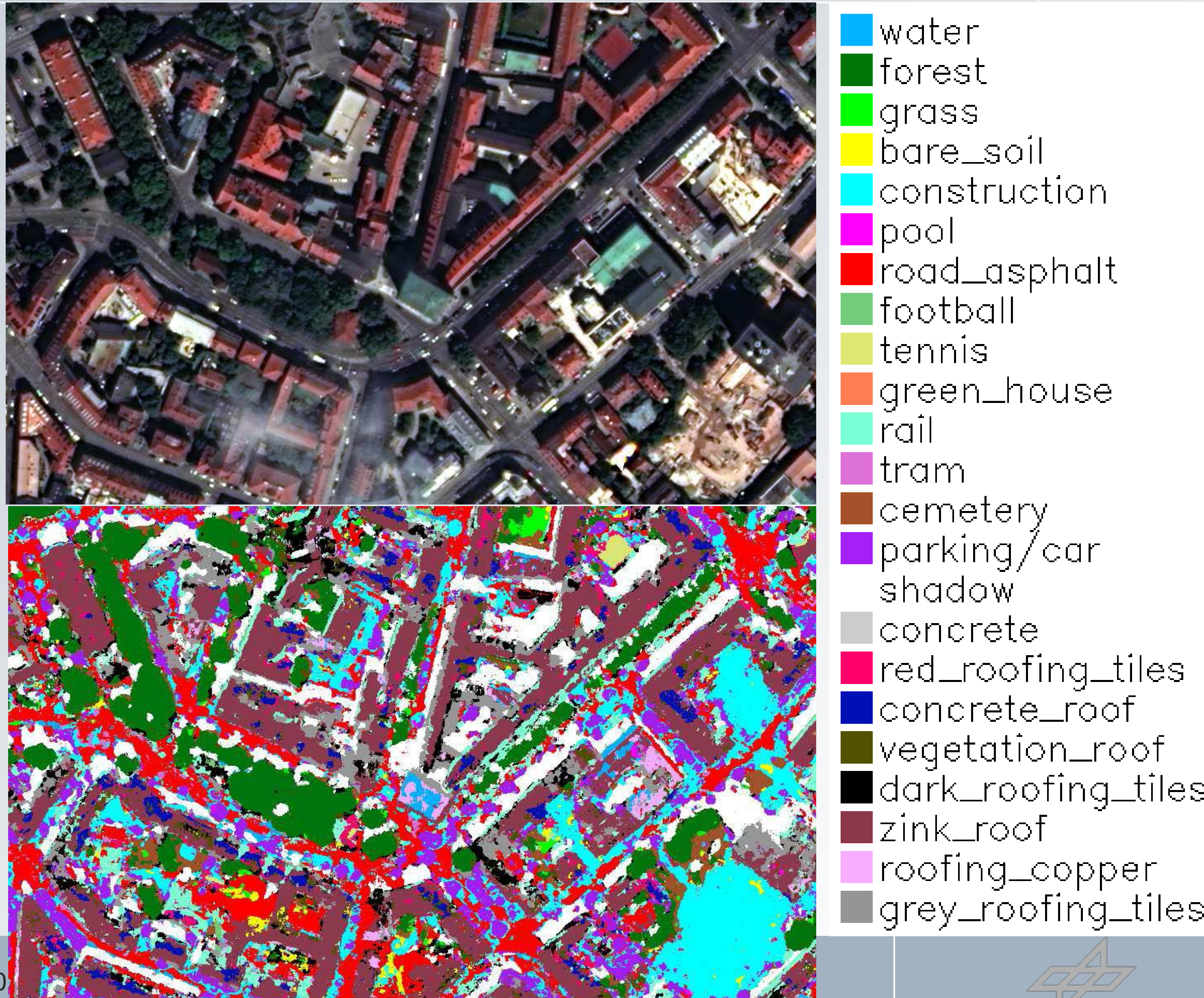

Influence of data sources on classification

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Confused classes		Sensor or feature influence for proper classification
Class 1	Class 2	Sensor/Feature
Road	Building	DSM
Rail road/Tram road	Road	SAR Texture
Rail road	Tram road	SAR Texture
Bare soil	Construction site	SAR Texture
Football field	Grass/Low vegetation	SAR Texture, Multispectral
Parking/car	Road	Texture on optical data
Cemetery	Grass/Low vegetation	SAR Texture
Green house	Road	SAR Texture, Multispectral

Simulation

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- Pre-processing
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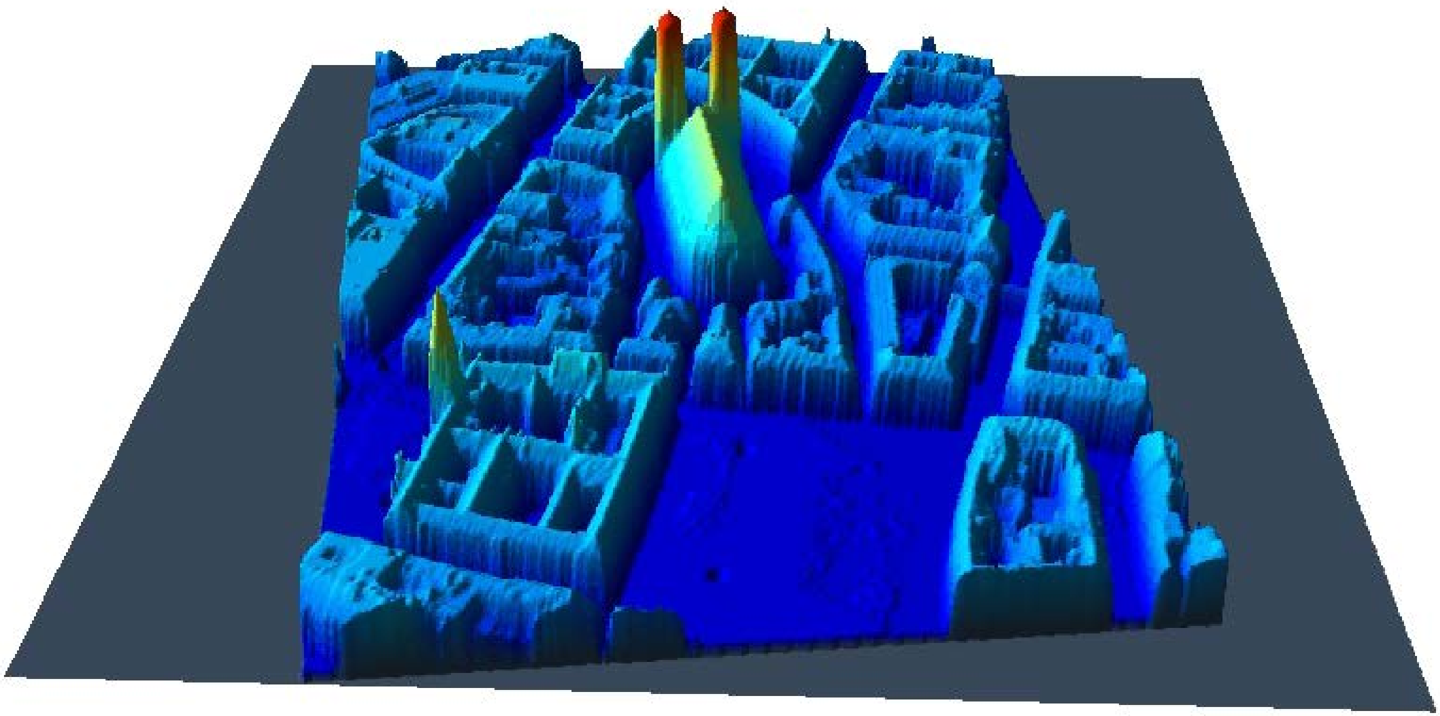
Laser DSM



Horizontal resolution: 1m
vertical resolution: 0.1m

Simulation optical/SAR images

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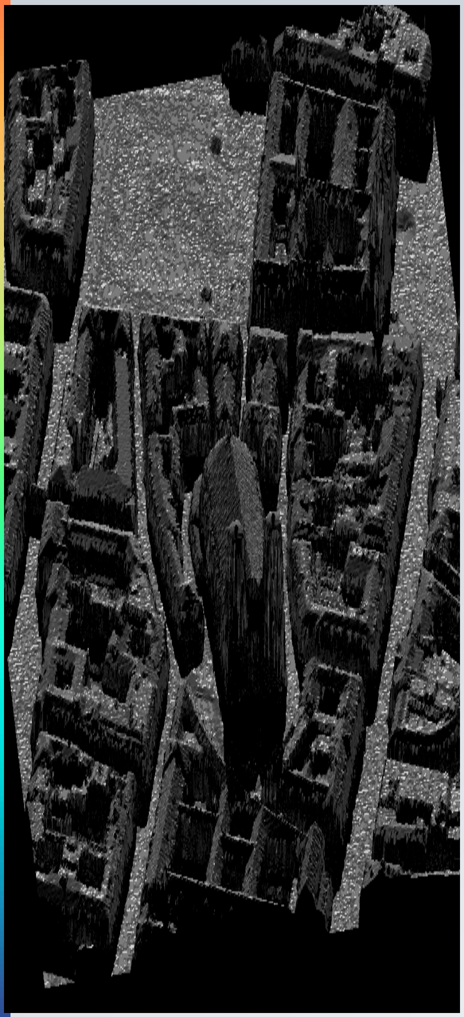
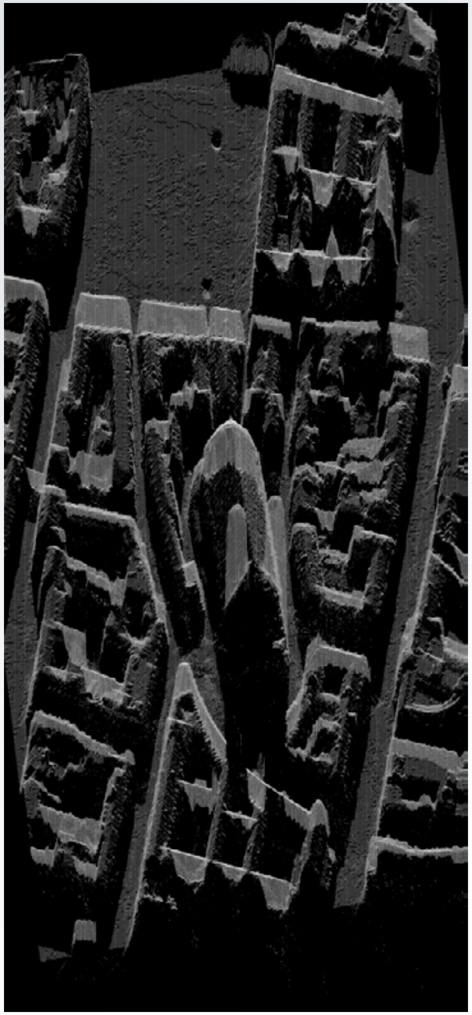


Simulated optical image

WV-1 image

TS-X image



Simulated SAR image

Single building extraction from DSM

1.FK_LS

2.FK_haus

3.FK_road

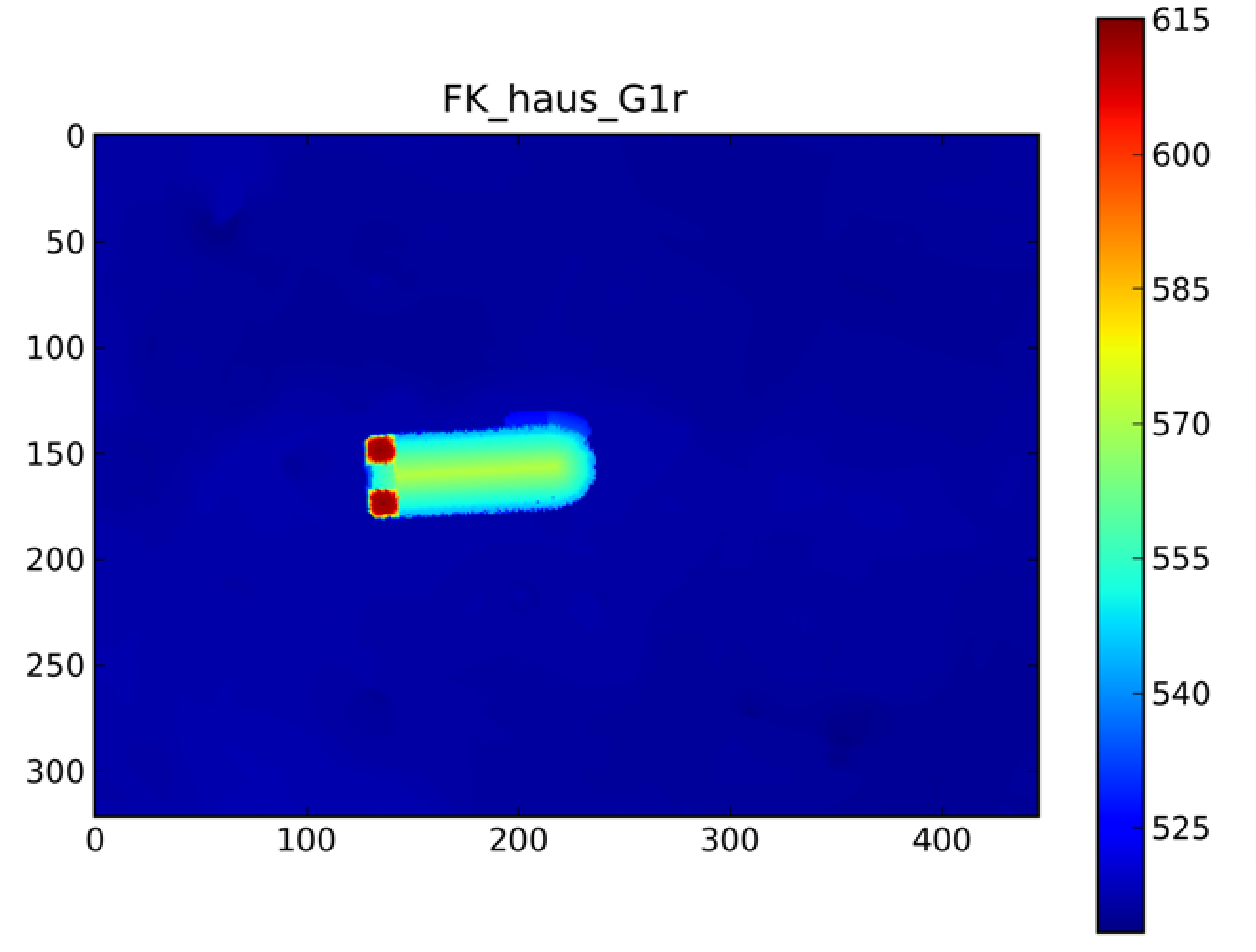
4.FK_road_median

5.FK_road_median_idw

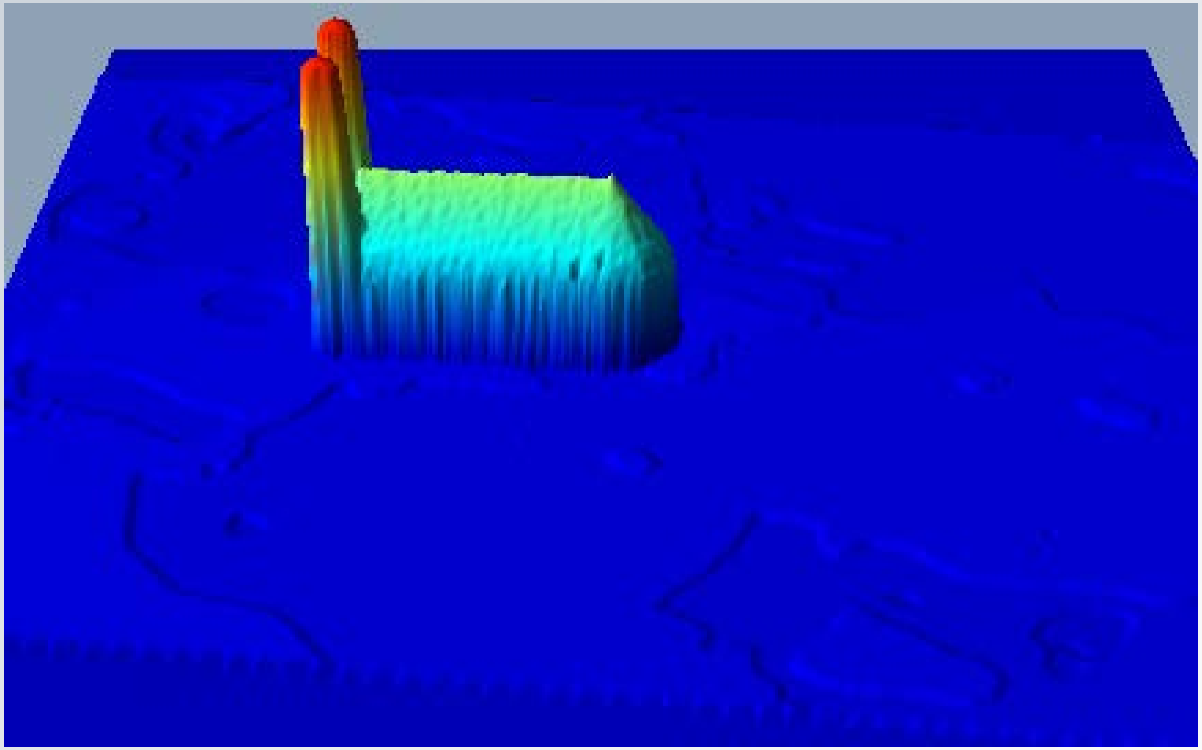
6.FK_haus_G1m

7.FK_haus_G1

8.FK_haus_G1r

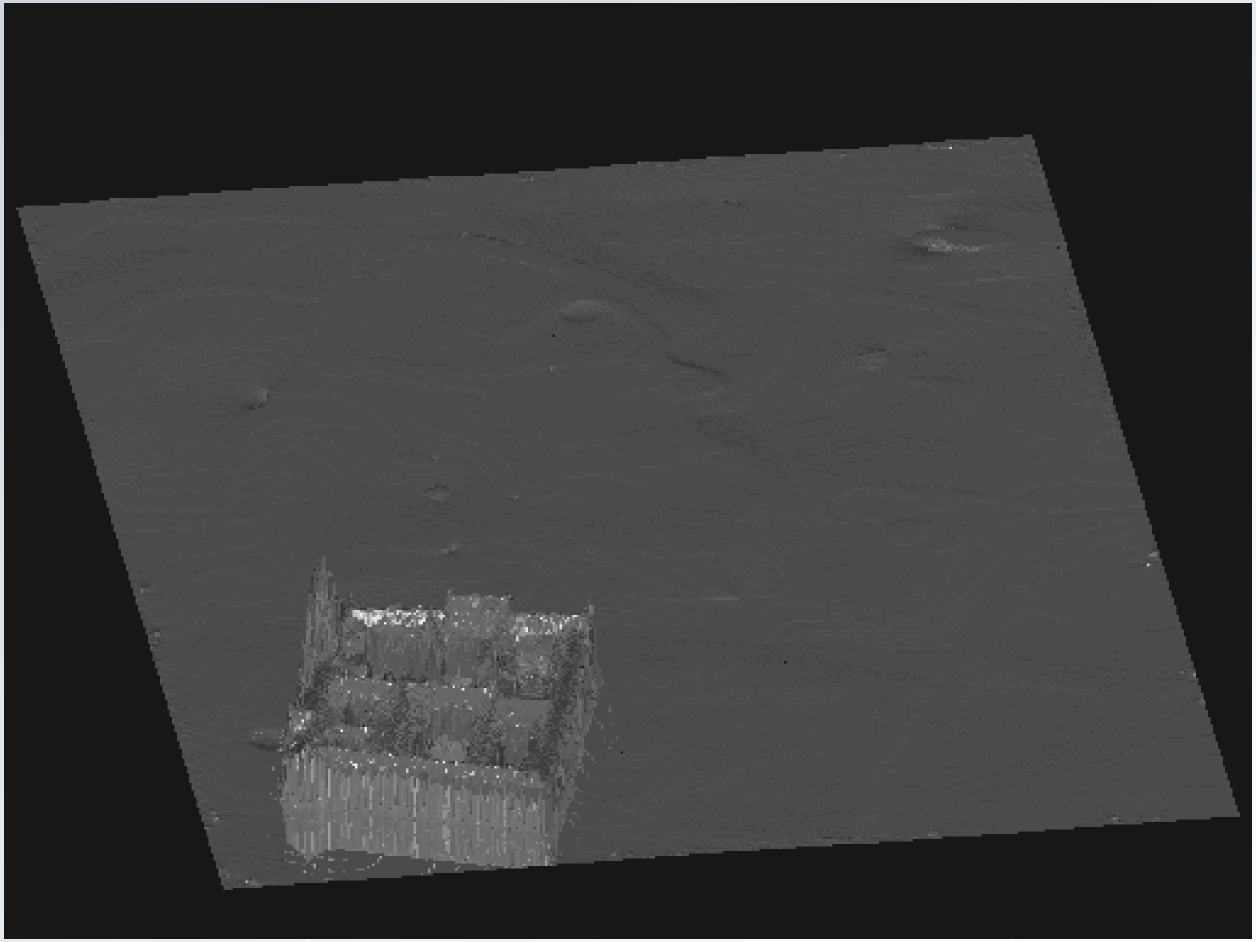


Single building model

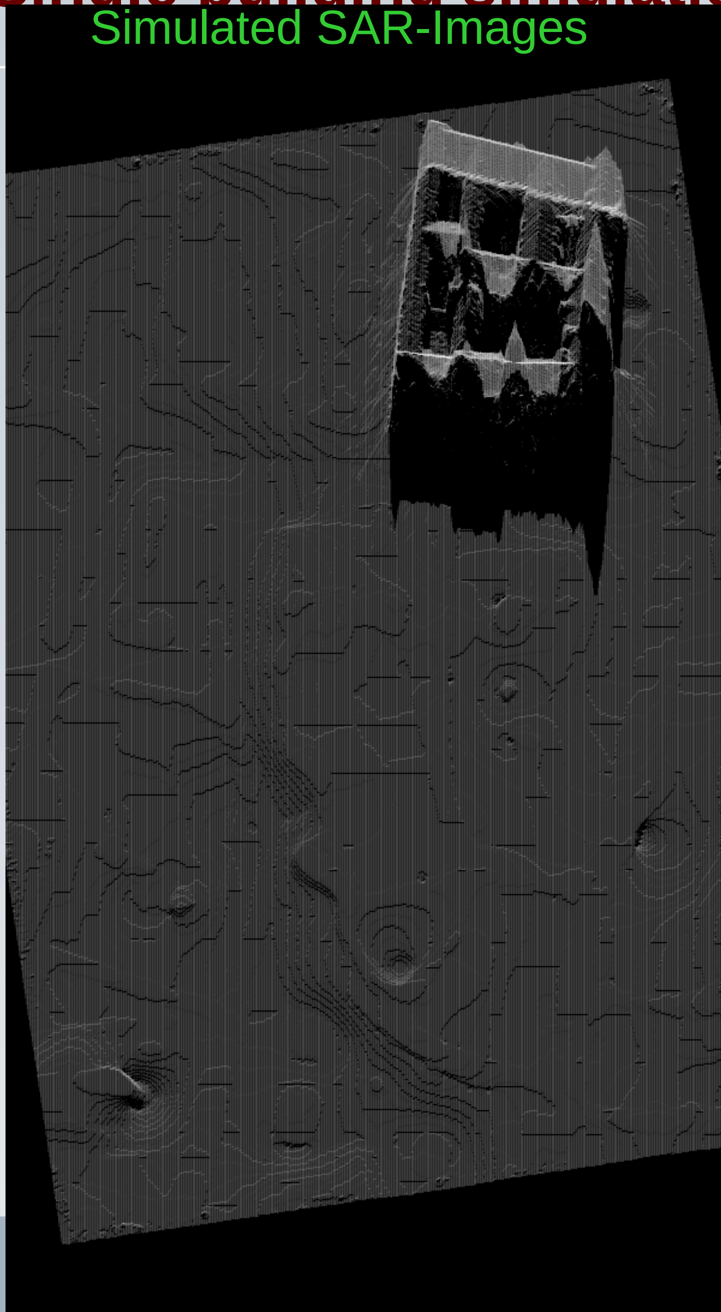


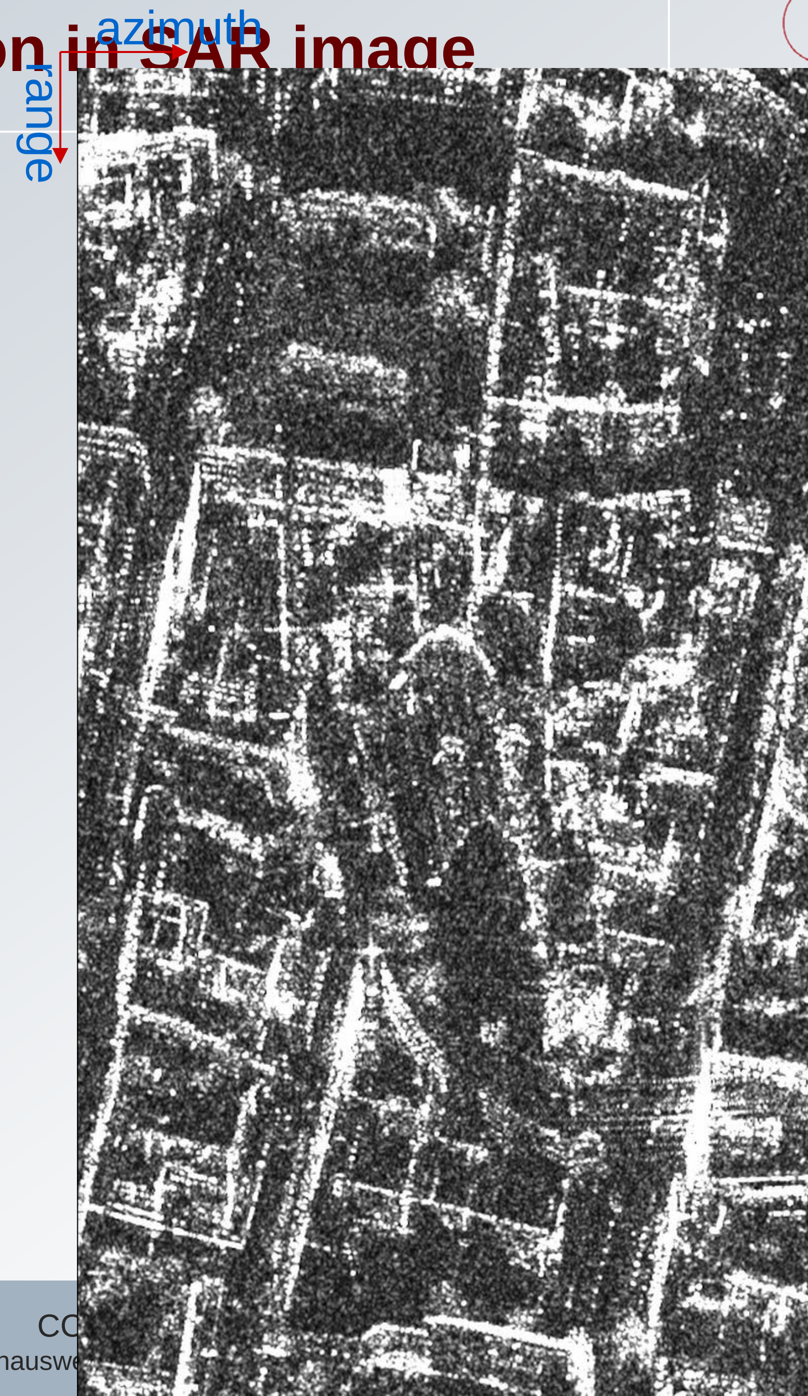
DEM + single building model

Single building simulation in optical image



Single building simulation in SAR image





Line extraction in TS-X image

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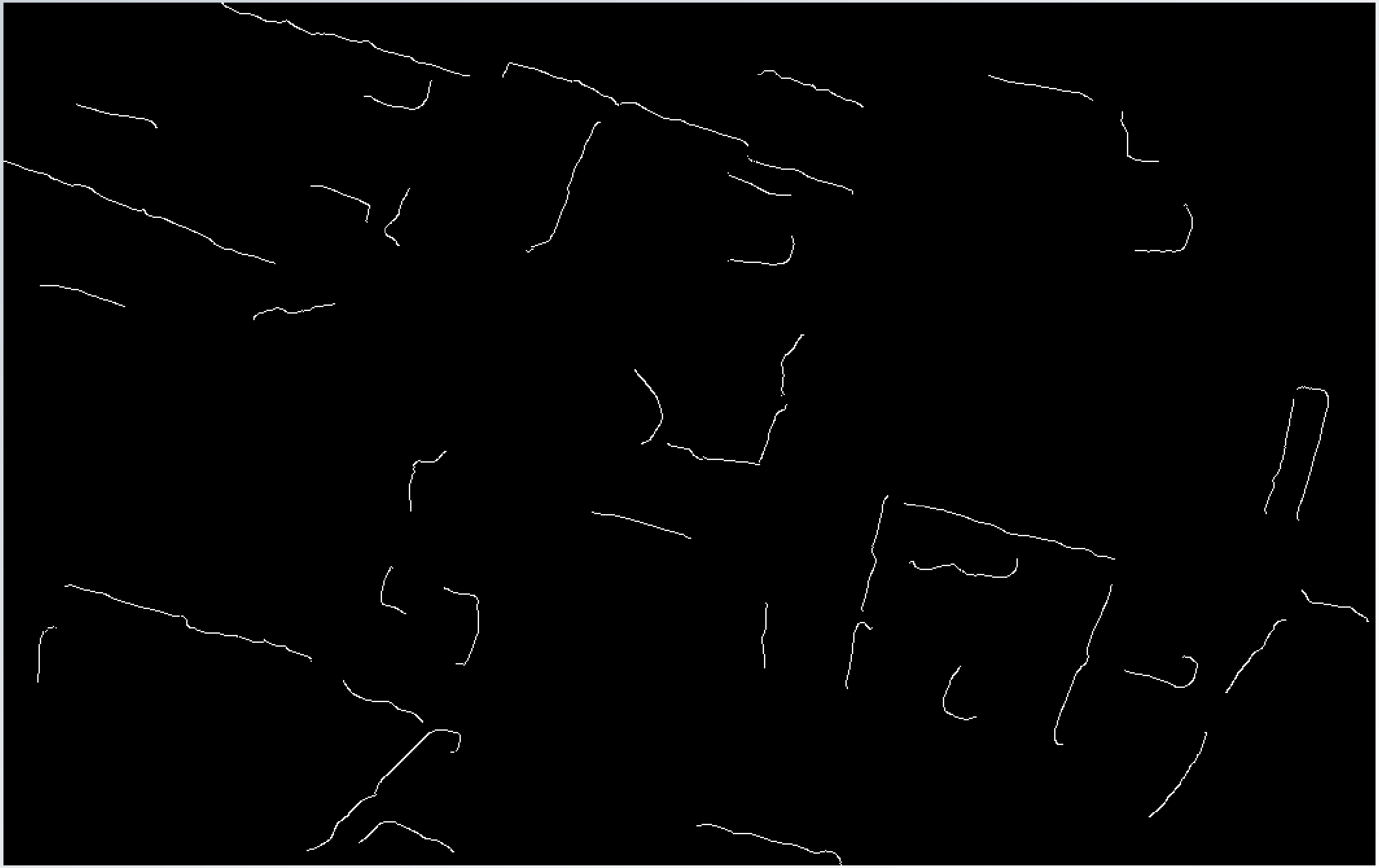
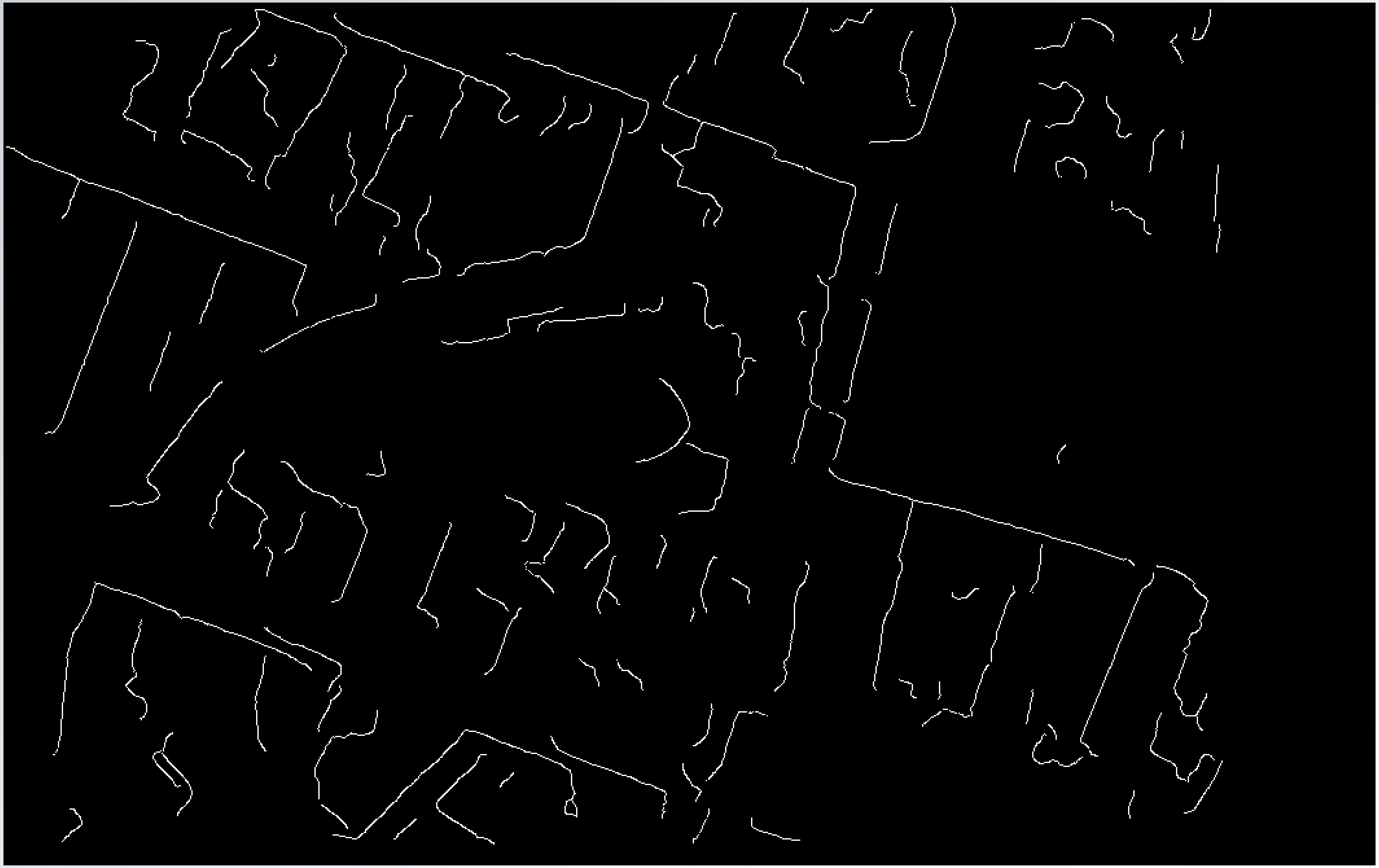
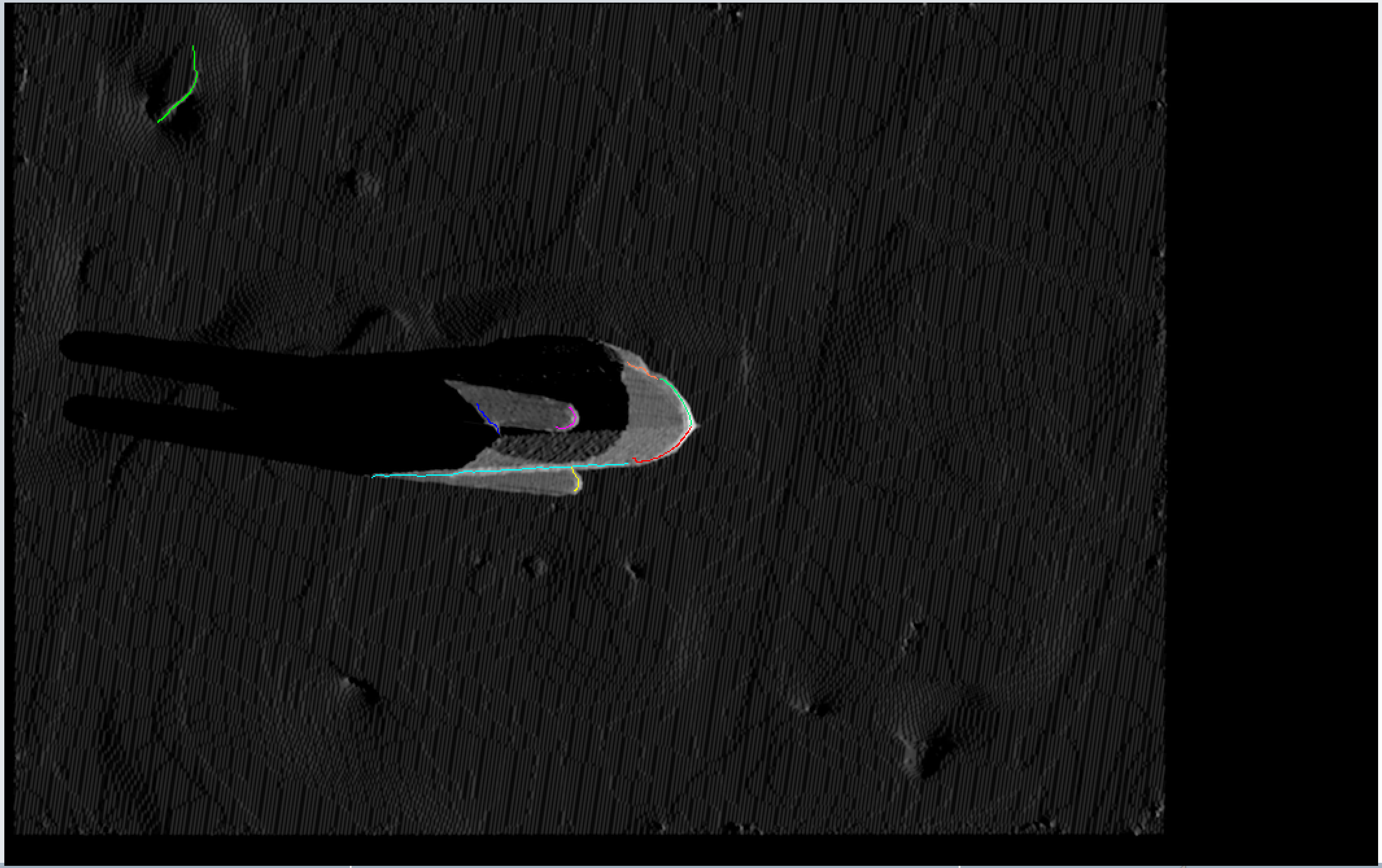


Line extraction in simulated image



Line extraction for single building



Extracted lines

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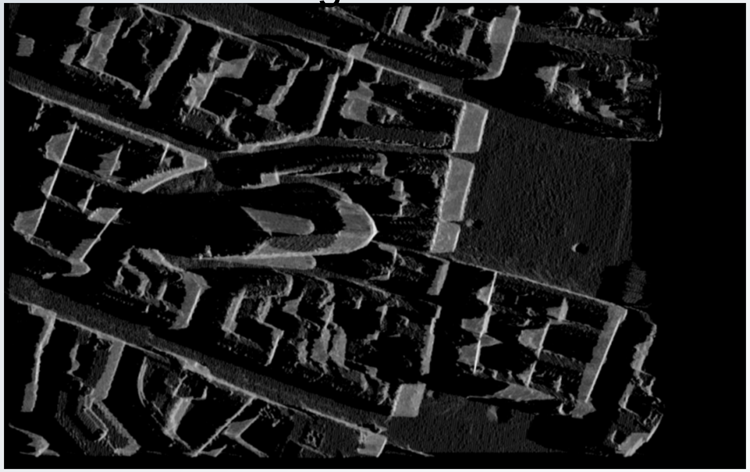
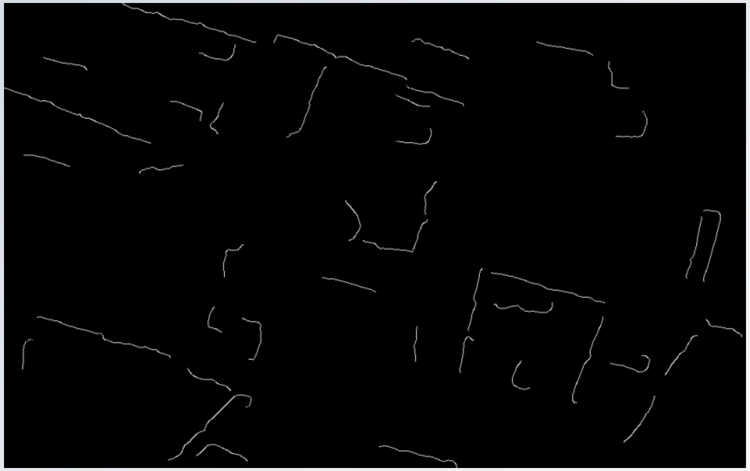
TSX image

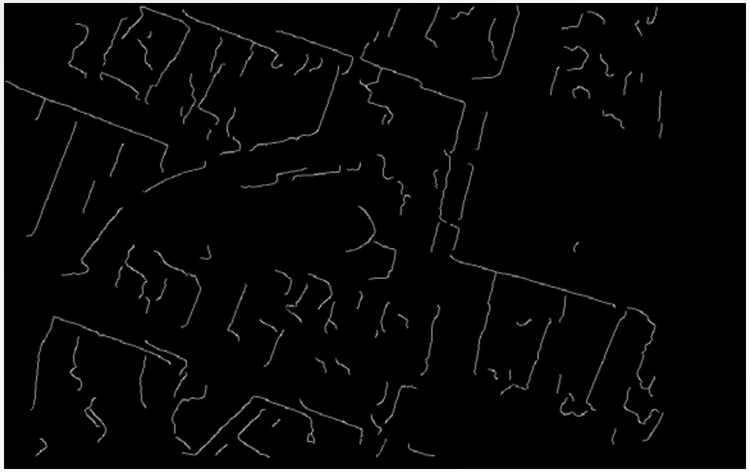
Simulated image

image



Extracted line features





Lines matching

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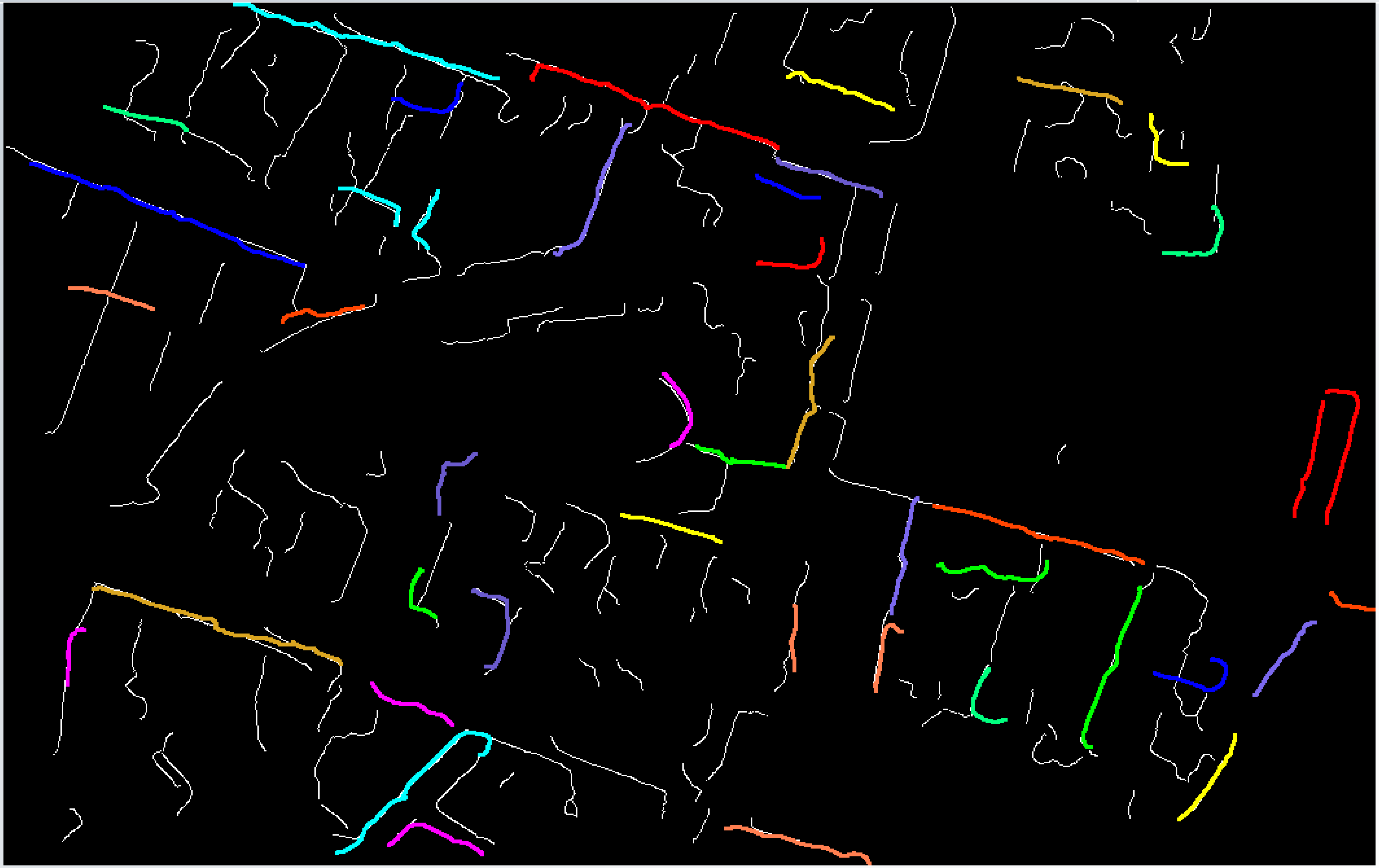

Lines from TSX (highlighted in colour)
Lines from simulated image (white)

Scene interpretation

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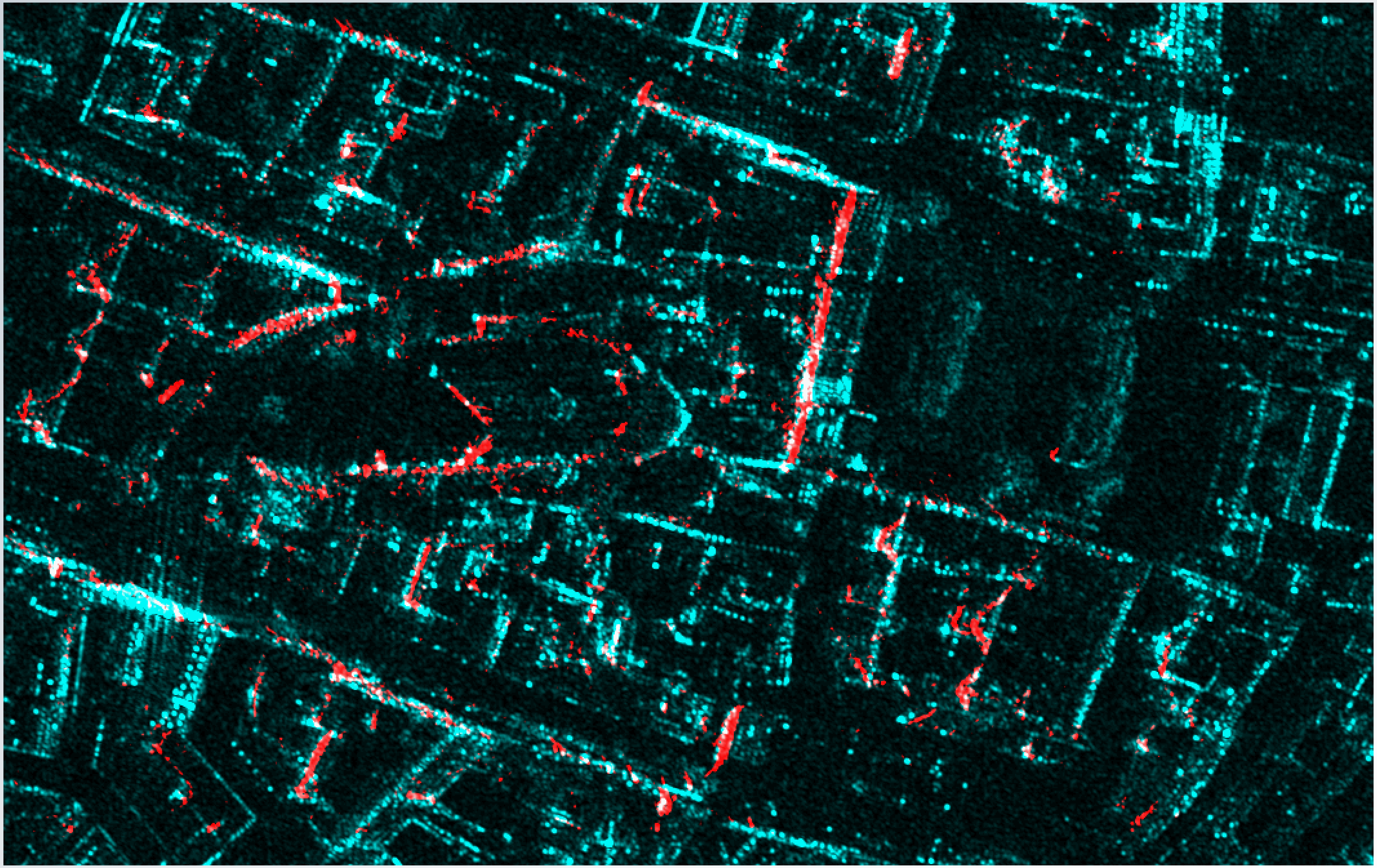

TSX (cyan), Simulated image (red)

Single building interpretation

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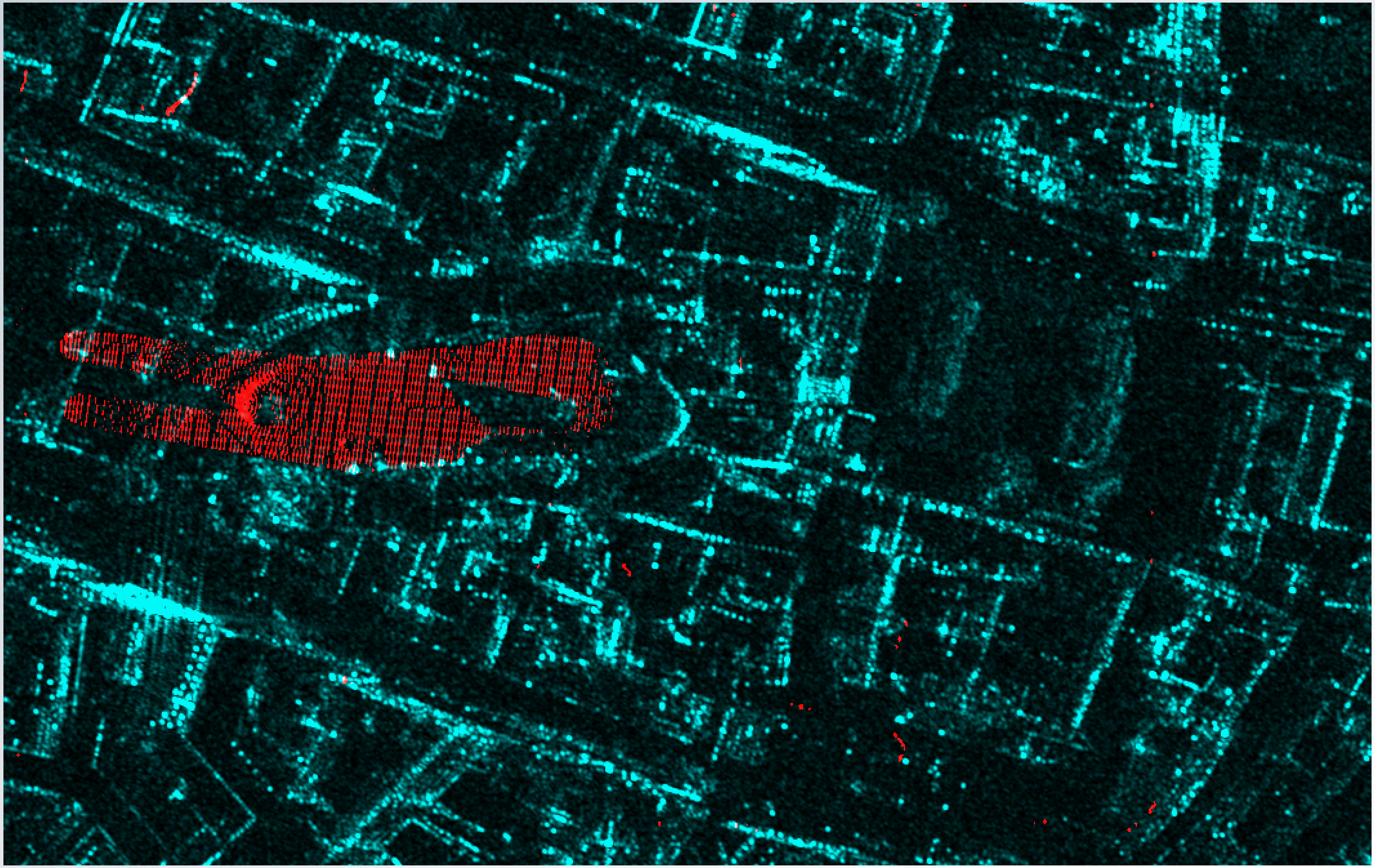

TSX (cyan), reflection and shadow area of single building model (red)

Conclusions

- Data fusion concept is introduced
- Acquisition geometry should be considered
- Data preparation is very important
- General fusion framework GFF introduced
- Data fusion framework INFOFUSE introduced
  - Suitable for multi-sensor data classification
  - Separate feature processing and representation on a finite discrete domain allows to reduce storage and processor requirements
  - Classification process is not restricted by data size
- Examples for WV-2 and TS-X joint urban area classification are presented
  - SAR features help to resolve road/building confusion
  - Increase number of urban classes
  - Increase classification accuracy

Conclusions II

Problems

- Influence of shadowing (mostly self shadows) on classification accuracy and material confusion
- Time gap of sensors acquisition – possible confusion of classes but prospects for class-specific change detection
- Dependency on acquisition time for different imaging sensors

Future work

- Orthogonal acquisition model for optical and SAR data
- Employment of the model for class-specific change detection on single or multisensory data
- A proper validation methodology is required

Conclusions III

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- Simulated optical image for direct and quick identification of objects in the SAR image
- Simulated SAR images present single or multiple scattering in the SAR images, useful for building recognition and reconstruction
- Orthorectification enables a direct comparison with the SAR images
- Automatic matching with SAR Image
  - Line group matching

Future work

  - Change detection between DSM and SAR

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